Branching Networks II

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Principles of Complex Systems, Vols. 1, 2, & 3D
CSYS/MATH 6701, 6713, & a pretend number, 2024–2025

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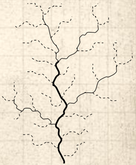
Computational Story Lab | Vermont Complex Systems Center
Santa Fe Institute | University of Vermont



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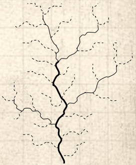

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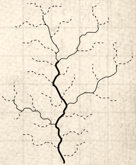
Outline




THE SUN
THE GOLDEN AGE OF REDUCTIONISM
THE MANIFESTO
WELL OF SCALES
THE LAWS OF DECAYING POWER
THE UNEXPECTED TRANSFIGURATION
MINISTRY OF RANDOM WALKS
THE RICH GET RICHER
THE DREAM OF EFFICIENT LANGUAGE
THE LAW OF DIGITS FIRST
THE SURPRISE OF BEING ROBUST YET FRAGILE
THE MISREADING OF THE BOOK OF SAND
THE MANY TAILS OF MANY TAILS
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THE POURING DATA
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THE EMERGENCE OF DESTRUCTION
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THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
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THE BIRDS OF A FEATHER
THE BIRDS OF NOT A FEATHER
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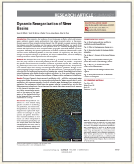
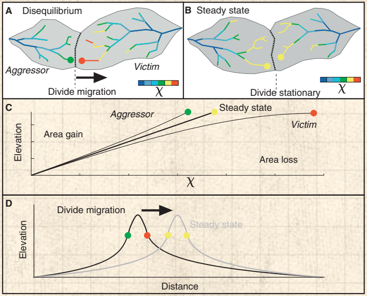
THE SCRYING FOR THE SHAPES OF THINGS
THE LIMITS OF ORGANIZATIONS


THE LANDSCAPES OF FORKING PATHS

Piracy on the high χ's:



"Dynamic Reorganization of River Basins"
Willett et al.,
Science, **343**, 1248765, 2014. [21]



$$\frac{\partial z(x,t)}{\partial t} = U - K A^m \left| \frac{\partial z(x,t)}{\partial x} \right|^n$$

$$z(x) = z_\mathrm{b} + \left(\frac{U}{K A_0^m} \right)^{1/n} \chi$$

$$\chi = \int_{x_\mathrm{b}}^{x} \left(\frac{A_0}{A(x')} \right)^{m/n} \mathrm{d}x'$$

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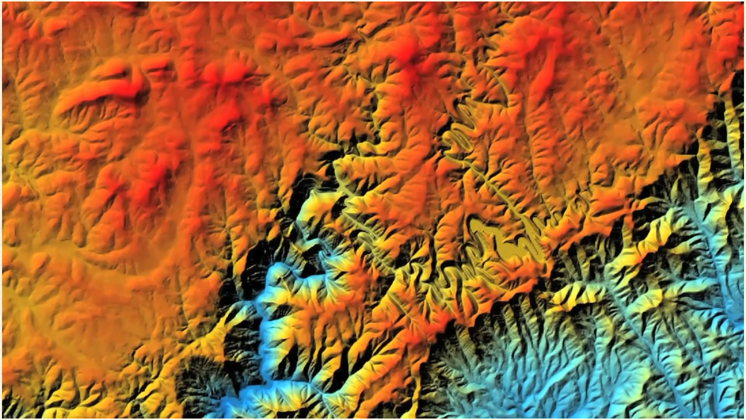
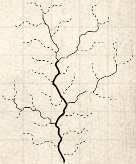


Story: How river networks move across a landscape (Science Daily)



Source: https://www.youtube.com/watch?v=FnroL1_-l2c


The Sun
The Golden Age of Reductionism
The Manifesto
The Well of Scales
The Laws of Decaying Power
The Unexpected Transfiguration
Ministry of Random Walks
The Rich Get Richer
The Dream of Efficient Language
The Law of Digits First
The Surprise of Being Robust yet Fragile
The Misreading of the Book of Sand
The Many Tails of Many Tails
The Measuring
The Data Poor
The Pouring Data
The Charms of the Many Wrong Paths
The Books That Should Not Be Opened
The Knowledge of Dead Monks
The Emergence of Structure
The Emergence of Destruction
The Emergence of Thinking
The Emergence of Stories
The Mechanics Statistical
The Thresholds of Percolation
The Networks Complex
The Elements of Webs
The Birds of a Feather
The Birds of Not a Feather
The Ark of the Random Network
The Strangeness of Friends
The Smallness of Worlds
The Theory of Six Degrees
The Networks Free of Scale
The Contagion
The Confusion of Contagions
The Disease of Random Mixing
The Unending Pandemics
The Thresholds of the Mind
The Social Wild
The Social Contagion
The Ratio of Gain
The Mechanics of Fame
The Talk of Fame
The Stories Contagious
The John Dory
The Adjacent Narratives
The Storytellers
The Fated Astral Path
The Paths of Universality
The Dependent Paths
The Trousers of Bifurcating Realities
The Unknown Mechanism
The Landscapes of Forking Paths
The Networks of Blood
The Trees of Reality
The Orders of Streams
The Scaling of Broken Hierarchies
The Braid or the Branch
The Law of Optimal Forks
The Church of Quarterology
The Truthicide
The Family of Pancake Cows
The Family of Spherical Cows
The Improbable Pachyderm
The Ill-Scaling of Allometric Bodies
The Supply Most Fair
The Supply to the Most
The Dark Art of Generating Functions
The Random Sum of Randomness
The Two-Sided Worlds
The Stories and the Tropes
The Truth of Diffusion
The Unveiling of Hidden Powers
The Scrying for the Shapes of Things
The Limits of Organizations


The Laws of Branching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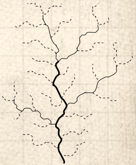
THE SCALING OF BROKEN HIERARCHIES

Can Horton and Tokunaga be happy?

Horton and Tokunaga seem different:



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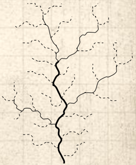

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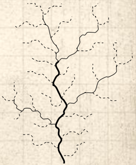

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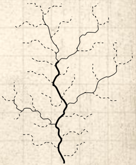
- R_n, R_a, R_ℓ, and R_s versus T_1 and R_T. One simple redundancy: $R_\ell = R_s$.
  Insert assignment question



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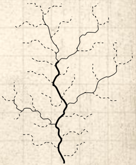

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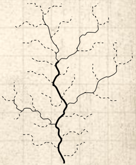
- Known result: Tokunaga → Horton [18, 19, 20, 9, 2]



Let us make them happy

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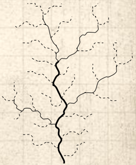
Space-fillingness



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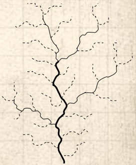

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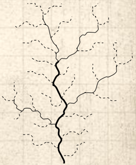
  Drainage density $\rho_{\rm dd}$ = inverse of typical distance between channels in a landscape.



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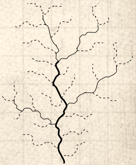
$$\rho_{\mathrm{dd}} \simeq \frac{\sum \text{stream segment lengths}}{\text{basin area}}$$



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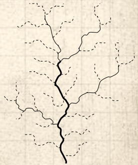

More with the happy-making thing

Start with Tokunaga's law: $T_k = T_1 R_T^{k-1}$

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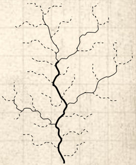

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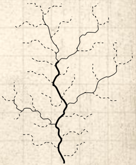
- Estimate n_ω, the number of streams of order ω in terms of other $n_{\omega'}, \omega' > \omega$.



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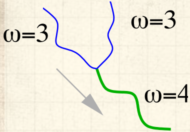

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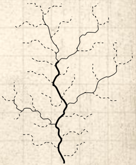

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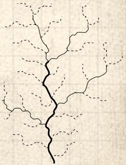

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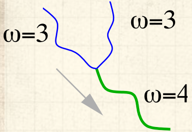

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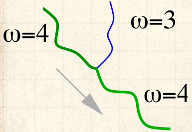

2. Running into and being absorbed by a stream of higher order $\omega' > \omega$ ...

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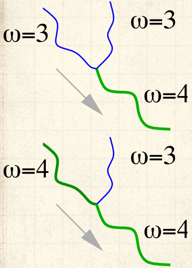

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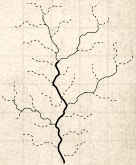

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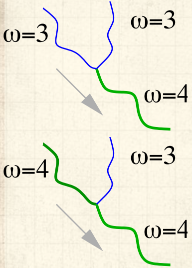

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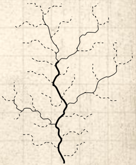
   - $n_{\omega'} T_{\omega' - \omega}$ streams of order ω do this



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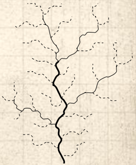

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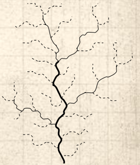
- Solution:

$$R_n = \frac{(2 + R_T + T_1) \pm \sqrt{(2 + R_T + T_1)^2 - 8R_T}}{2}$$

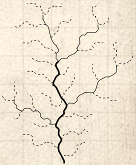
(The larger value is the one we want.)



Finding other Horton ratios

Connect Tokunaga to R_s

- Now use uniform drainage density ρ_{dd}.



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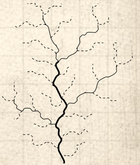

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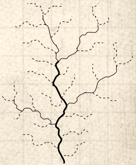

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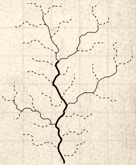

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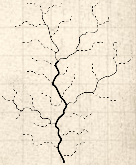

Horton and Tokunaga are happy

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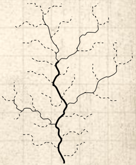
- And from before:

$$\boxed{R_n = \frac{(2 + R_T + T_1) + \sqrt{(2 + R_T + T_1)^2 - 8R_T}}{2}}$$



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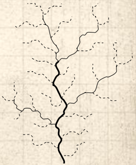
Some observations:

- R_n and R_ℓ depend on T_1 and R_T.



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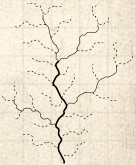

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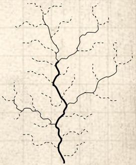

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- We'll in fact see that $R_a = R_n$.
- Also: Both Tokunaga's law and Horton's laws can be generalized to relationships between non-trivial statistical distributions. [3, 4]

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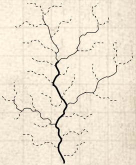

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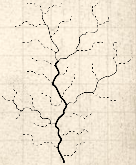

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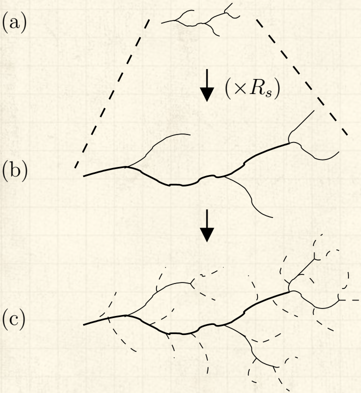
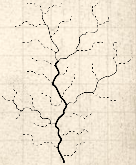
- Suggests we should be able to argue that Horton's laws imply Tokunaga's laws (if drainage density is uniform) ...

Horton and Tokunaga are friends

From Horton to Tokunaga [2]





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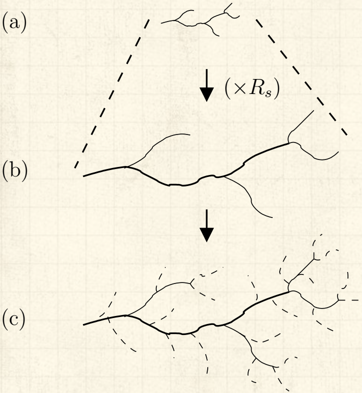

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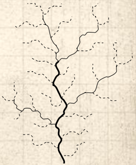

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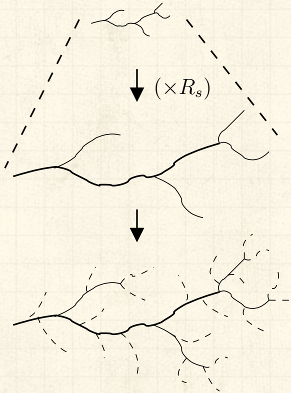
From Horton to Tokunaga [2]

(a)
(b)
(c)



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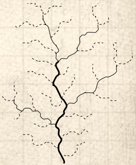

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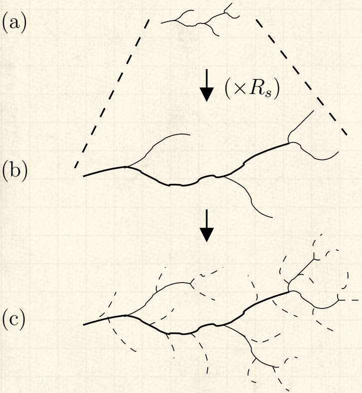

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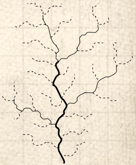

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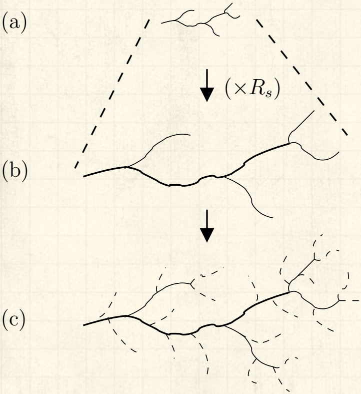

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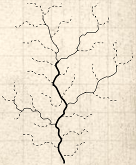

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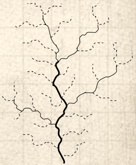

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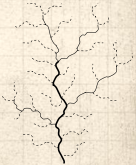

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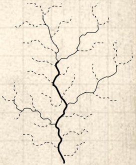

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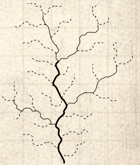

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- For large ω, Tokunaga's law is the solution—let's check ...

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Just checking:

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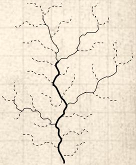

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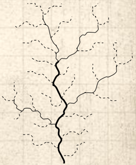

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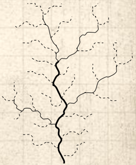

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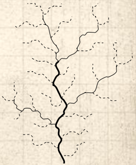

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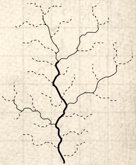
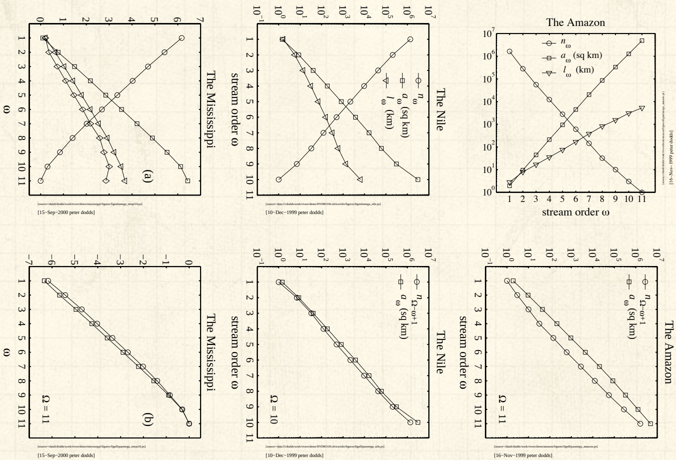
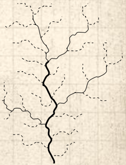
$$\simeq (R_\ell - 1) T_1 \frac{R_\ell^{k-1}}{R_\ell - 1} = T_1 R_\ell^{k-1}$$ ...yep.



Horton's laws of area and number:



- In bottom plots, stream number graph has been flipped vertically.
- Highly suggestive that $R_n \equiv R_a$ ...



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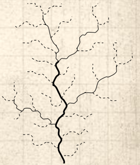
- How robust are our estimates of ratios?
- Rule of thumb: discard data for two smallest and two largest orders.

Mississippi:

ω range	R_n	R_a	R_ℓ	R_s	R_a/R_n
$[2,3]$	5.27	5.26	2.48	2.30	1.00
$[2,5]$	4.86	4.96	2.42	2.31	1.02
$[2,7]$	4.77	4.88	2.40	2.31	1.02
$[3,4]$	4.72	4.91	2.41	2.34	1.04
$[3,6]$	4.70	4.83	2.40	2.35	1.03
$[3,8]$	4.60	4.79	2.38	2.34	1.04
$[4,6]$	4.69	4.81	2.40	2.36	1.02
$[4,8]$	4.57	4.77	2.38	2.34	1.05
$[5,7]$	4.68	4.83	2.36	2.29	1.03
$[6,7]$	4.63	4.76	2.30	2.16	1.03
$[7,8]$	4.16	4.67	2.41	2.56	1.12
mean μ	4.69	4.85	2.40	2.33	1.04
std dev σ	0.21	0.13	0.04	0.07	0.03
σ/μ	0.045	0.027	0.015	0.031	0.024



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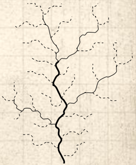
ω range	R_n	R_a	R_ℓ	R_s	R_a/R_n
[2, 3]	4.78	4.71	2.47	2.08	0.99
[2, 5]	4.55	4.58	2.32	2.12	1.01
[2, 7]	4.42	4.53	2.24	2.10	1.02
[3, 5]	4.45	4.52	2.26	2.14	1.01
[3, 7]	4.35	4.49	2.20	2.10	1.03
[4, 6]	4.38	4.54	2.22	2.18	1.03
[5, 6]	4.38	4.62	2.22	2.21	1.06
[6, 7]	4.08	4.27	2.05	1.83	1.05
mean μ	4.42	4.53	2.25	2.10	1.02
std dev σ	0.17	0.10	0.10	0.09	0.02
σ/μ	0.038	0.023	0.045	0.042	0.019



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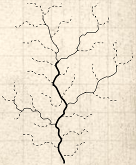

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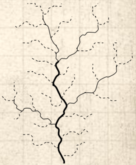

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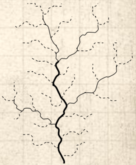

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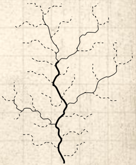

Reducing Horton's laws:

Rough first effort to show $R_n \equiv R_a$:

- $a_\Omega \propto$ sum of all stream segment lengths in a order Ω basin (assuming uniform drainage density)
- So:

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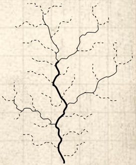

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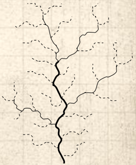

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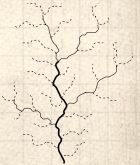

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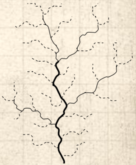
- So, a_Ω is growing like R_n^Ω and therefore:

$$\boxed{R_n \equiv R_a}$$



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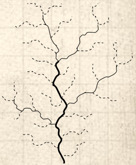

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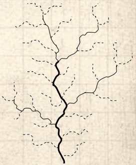
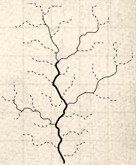
- Insert assignment question



Equipartitioning:



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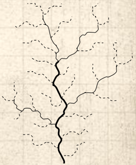

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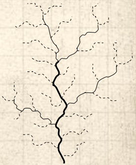
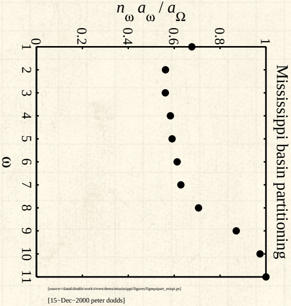
$$n_\omega \propto (R_n)^{-\omega}$$

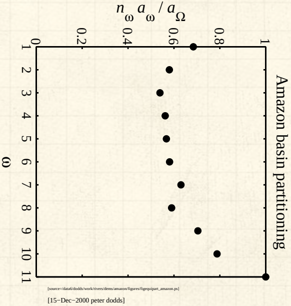
$$\bar{a}_\omega \propto (R_a)^{\omega} \propto n_\omega^{-1}$$

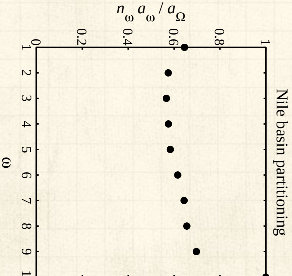


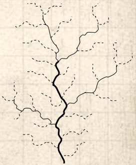
Equipartitioning:

Some examples:









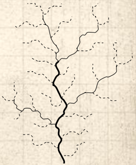
Neural Reboot: Fwoompf

https://www.youtube.com/watch?v=5mUs70SqD4o?rel=0

Scaling laws

The story so far:

Scaling laws



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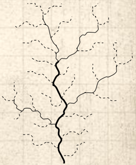

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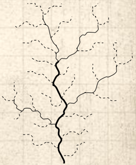

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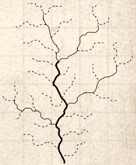

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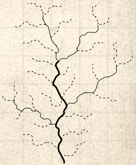

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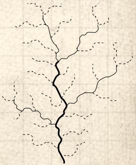

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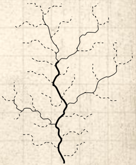

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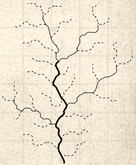

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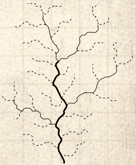

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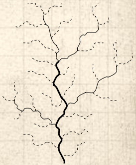

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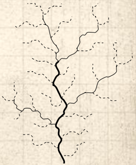

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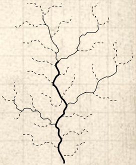

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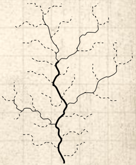

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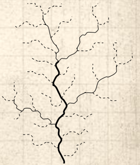

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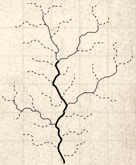

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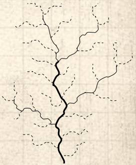

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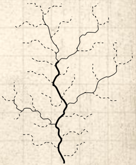

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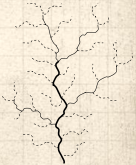

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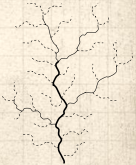

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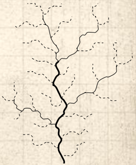

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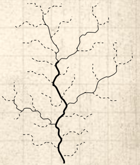

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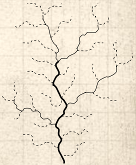

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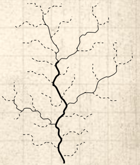

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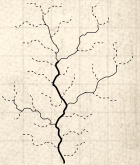

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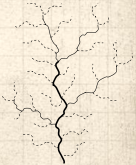

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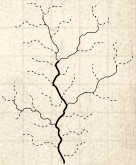

Scaling laws

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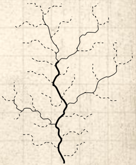
- Also known as the exceedance probability.



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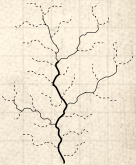

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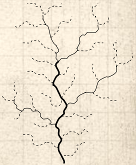

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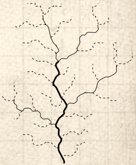
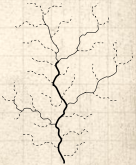


Scaling laws

Finding γ:

- Aim: determine probability of randomly choosing a point on a network with main stream length $> \ell_*$



Scaling laws

Finding γ:

- Aim: determine probability of randomly choosing a point on a network with main stream length $> \ell_*$
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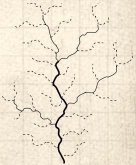
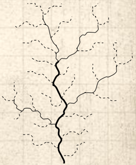


Scaling laws



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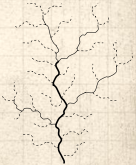

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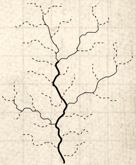
- Use Horton's law of stream segments: $\bar{s}_\omega / \bar{s}_{\omega-1} = R_s$ ...

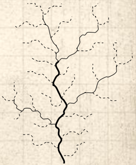


Scaling laws

Finding γ:

- Set $\ell_* = \overline{\ell}_\omega$ for some $1 \ll \omega \ll \Omega$.

Scaling laws



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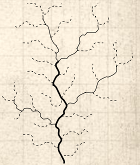

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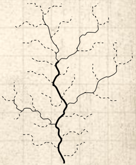

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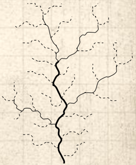

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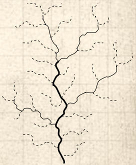

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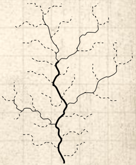

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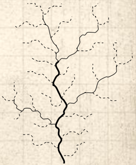
Scaling laws



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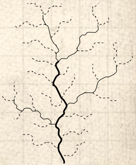

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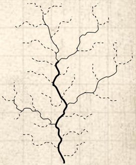

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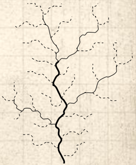

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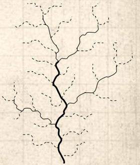

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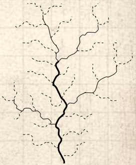

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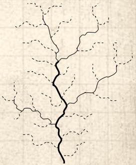

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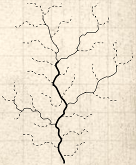

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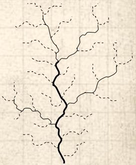

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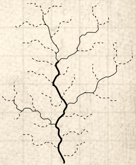

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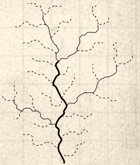

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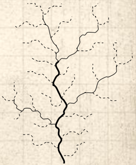
-

$$\bar{\ell}_\omega \propto R_\ell^\omega = R_s^\omega = e^{\omega \ln R_s}$$



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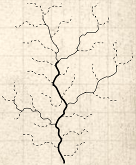

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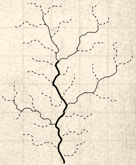

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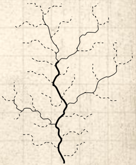

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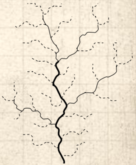

Scaling laws

Finding γ:

- Therefore:

$$P_>(\bar{\ell}_\omega) \propto e^{-\omega \ln(R_n/R_s)} = \left(e^{\omega \ln R_s}\right)^{-\ln(R_n/R_s)/\ln(R_s)}$$

- $$\propto \bar{\ell}_\omega^{\,-\ln(R_n/R_s)/\ln R_s}$$

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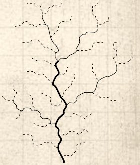

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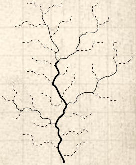

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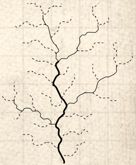
$$\tau = 2 - \ln R_s / \ln R_n = 2 - 1/\gamma$$

Insert assignment question



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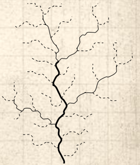

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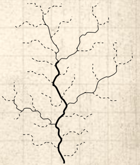
Insert assignment question

- Such connections between exponents are called scaling relations
- Let's connect to one last relationship: Hack's law



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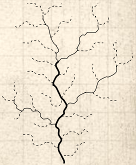
Hack's law: [6]

$$\ell \propto a^h$$



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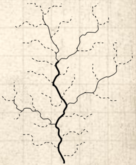

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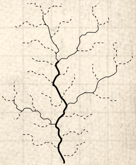

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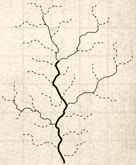

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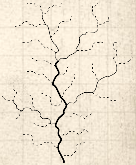

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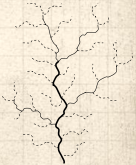

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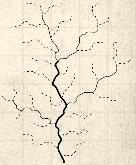
We mentioned there were a good number of 'laws': [2]

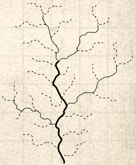
Relation:	Name or description:
$T_k = T_1(R_T)^{k-1}$	Tokunaga's law
$\ell \sim L^d$	self-affinity of single channels
$n_\omega / n_{\omega+1} = R_n$	Horton's law of stream numbers
$\bar{\ell}_{\omega+1} / \bar{\ell}_\omega = R_\ell$	Horton's law of main stream lengths
$\bar{a}_{\omega+1} / \bar{a}_\omega = R_a$	Horton's law of basin areas
$\bar{s}_{\omega+1} / \bar{s}_\omega = R_s$	Horton's law of stream segment lengths
$L_\perp \sim L^H$	scaling of basin widths
$P(a) \sim a^{-\tau}$	probability of basin areas
$P(\ell) \sim \ell^{-\gamma}$	probability of stream lengths
$\ell \sim a^h$	Hack's law
$a \sim L^D$	scaling of basin areas
$\Lambda \sim a^\beta$	Langbein's law
$\lambda \sim L^\varphi$	variation of Langbein's law



Connecting exponents

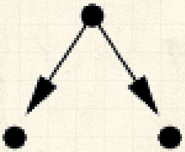
Only 3 parameters are independent:
e.g., take d, R_n, and R_s

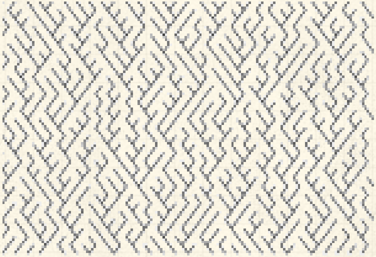
relation:	scaling relation/parameter: [2]
$\ell \sim L^d$	d
$T_k = T_1 (R_T)^{k-1}$	$T_1 = R_n - R_s - 2 + 2R_s/R_n$
	$R_T = R_s$
$n_\omega / n_{\omega+1} = R_n$	R_n
$\bar{a}_{\omega+1}/\bar{a}_\omega = R_a$	$R_a = R_n$
$\bar{\ell}_{\omega+1}/\bar{\ell}_\omega = R_\ell$	$R_\ell = R_s$
$\ell \sim a^h$	$h = \ln R_s / \ln R_n$
$a \sim L^D$	$D = d/h$
$L_\perp \sim L^H$	$H = d/h - 1$
$P(a) \sim a^{-\tau}$	$\tau = 2 - h$
$P(\ell) \sim \ell^{-\gamma}$	$\gamma = 1/h$
$\Lambda \sim a^\beta$	$\beta = 1 + h$
$\lambda \sim L^\varphi$	$\varphi = d$



Scheidegger's model

Directed random networks [11, 12]



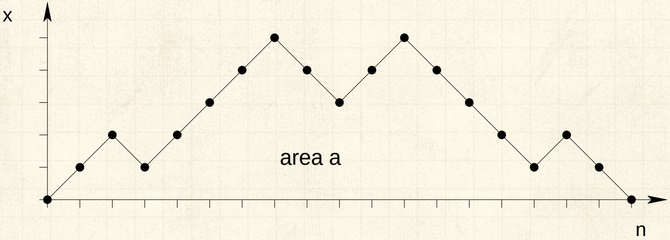


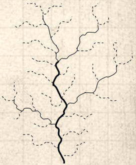
- $$P(\searrow) = P(\swarrow) = 1/2$$
- Functional form of all scaling laws exhibited but exponents differ from real world [15, 16, 14]
- Useful and interesting test case

A toy model—Scheidegger's model

Random walk basins:

- Boundaries of basins are random walks





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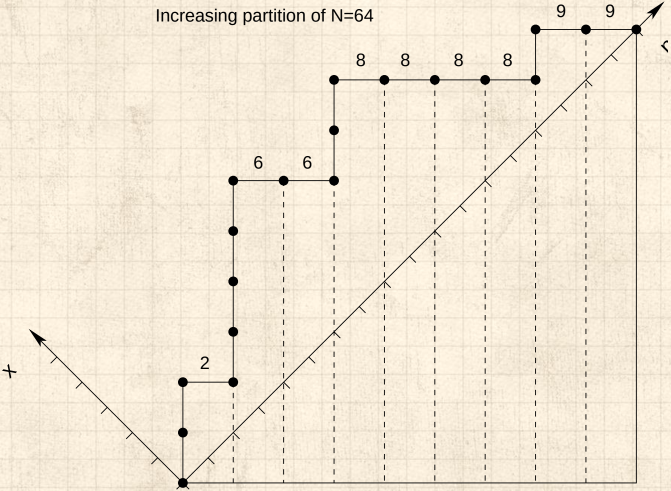

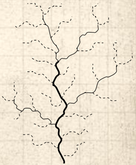

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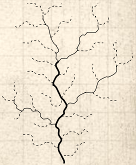

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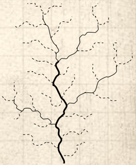

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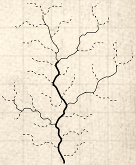
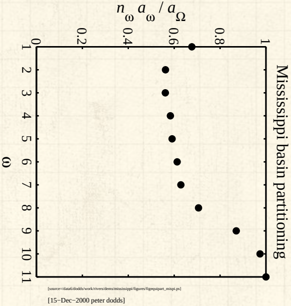
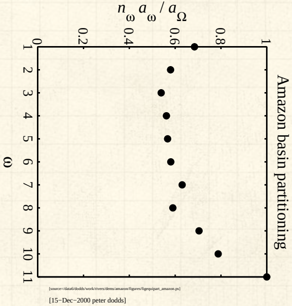
- R_n and R_ℓ have not been derived analytically.

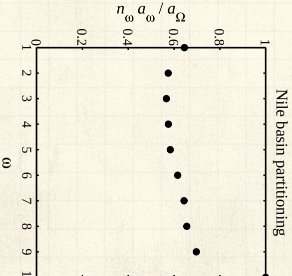


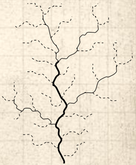
Equipartitioning reexamined:

Recall this story:









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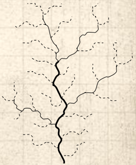

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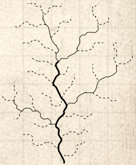

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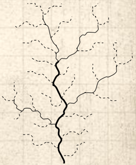
- while stream ordering separates basins ...



Fluctuations

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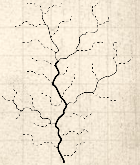

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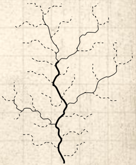

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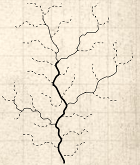
- See into the heart of randomness ...



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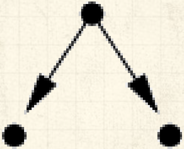

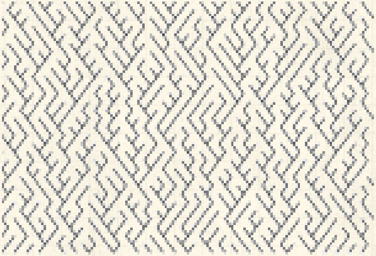

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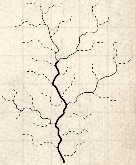
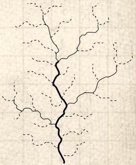
- Flow is directed downwards



Generalizing Horton's laws

- $\bar{\ell}_\omega \propto (R_\ell)^\omega \Rightarrow N(\ell|\omega) = (R_n R_\ell)^{-\omega} F_\ell(\ell/R_\ell^\omega)$



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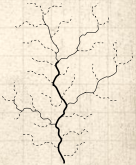

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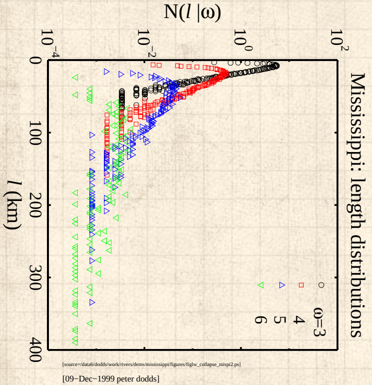

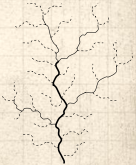

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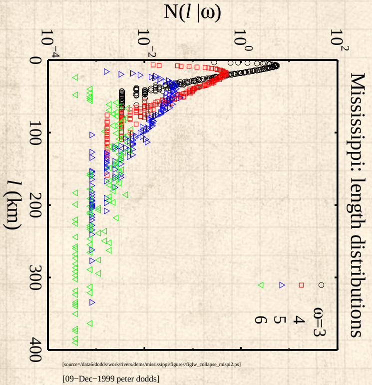
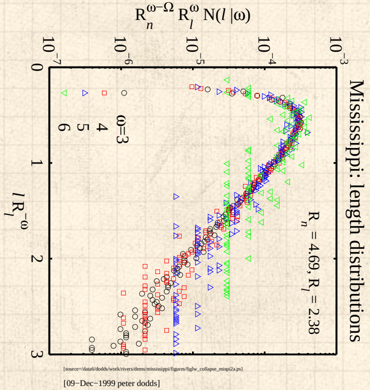
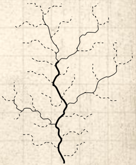




- Scaling collapse works well for intermediate orders



Generalizing Horton's laws

- $\bar{\ell}_\omega \propto (R_\ell)^\omega \Rightarrow N(\ell|\omega) = (R_n R_\ell)^{-\omega} F_\ell(\ell/R_\ell^\omega)$
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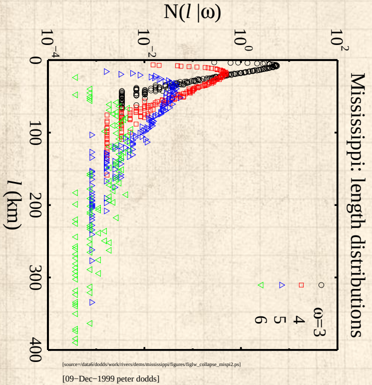
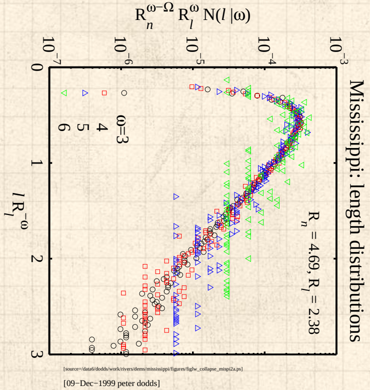
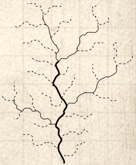


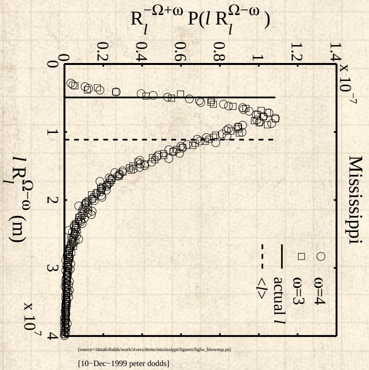


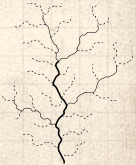
- Scaling collapse works well for intermediate orders
- All moments grow exponentially with order



Generalizing Horton's laws

- How well does overall basin fit internal pattern?





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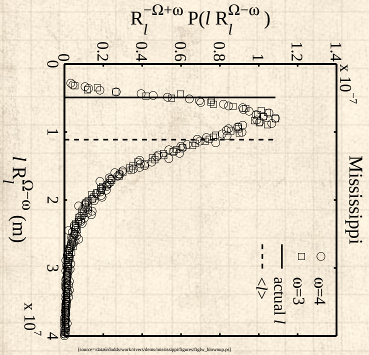
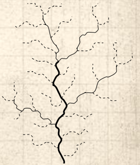


- Actual length = 4920 km (at 1 km res)



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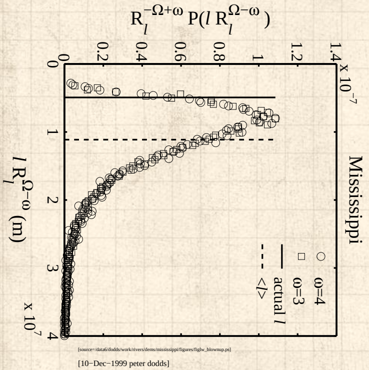
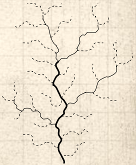


- Actual length = 4920 km (at 1 km res)
- Predicted Mean length = 11100 km



Generalizing Horton's laws

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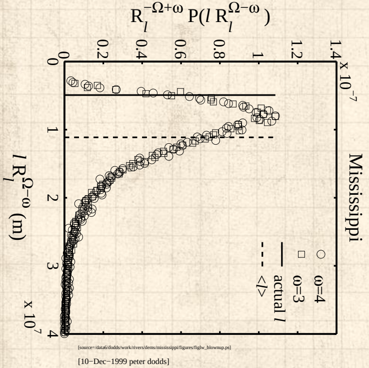
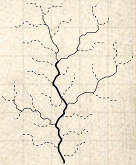


- Actual length = 4920 km (at 1 km res)
- Predicted Mean length = 11100 km
- Predicted Std dev = 5600 km



Generalizing Horton's laws

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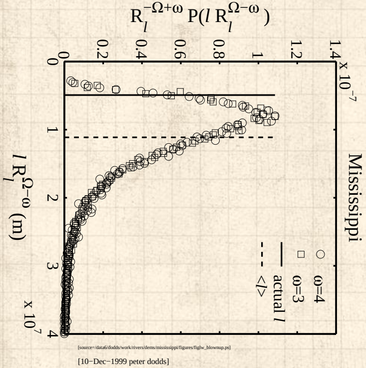

- Actual length = 4920 km (at 1 km res)
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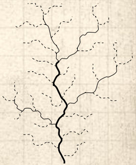
- Actual length/Mean length = 44 %



Generalizing Horton's laws

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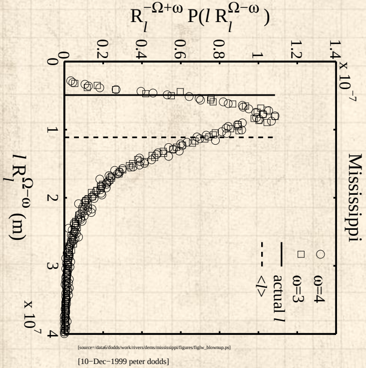

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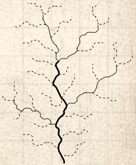
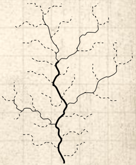
- Predicted Std dev = 5600 km
- Actual length/Mean length = 44 %
- Okay.



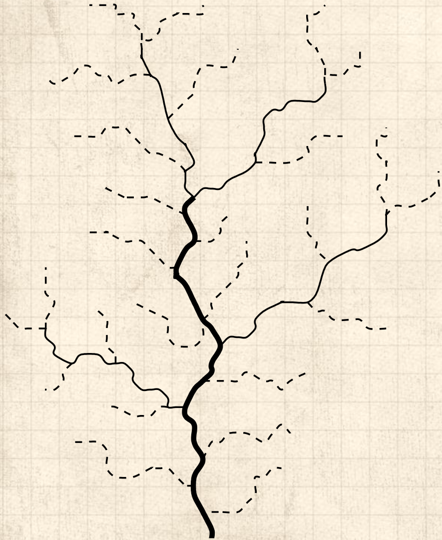
Generalizing Horton's laws

Comparison of predicted versus measured main stream lengths for large scale river networks (in 10^3 km):

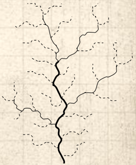
basin:	ℓ_Ω	$\bar{\ell}_\Omega$	σ_ℓ	$\ell_\Omega/\bar{\ell}_\Omega$	$\sigma_\ell/\bar{\ell}_\Omega$
Mississippi	4.92	11.10	5.60	0.44	0.51
Amazon	5.75	9.18	6.85	0.63	0.75
Nile	6.49	2.66	2.20	2.44	0.83
Congo	5.07	10.13	5.75	0.50	0.57
Kansas	1.07	2.37	1.74	0.45	0.73
	a_Ω	$\bar{a}_\Omega$	σ_a	$a_\Omega/\bar{a}_\Omega$	$\sigma_a/\bar{a}_\Omega$
Mississippi	2.74	7.55	5.58	0.36	0.74
Amazon	5.40	9.07	8.04	0.60	0.89
Nile	3.08	0.96	0.79	3.19	0.82
Congo	3.70	10.09	8.28	0.37	0.82
Kansas	0.14	0.49	0.42	0.28	0.86



Combining stream segments distributions:



- Stream segments sum to give main stream lengths
- $$\ell_\omega = \sum_{\mu=1}^{\mu=\omega} s_\mu$$



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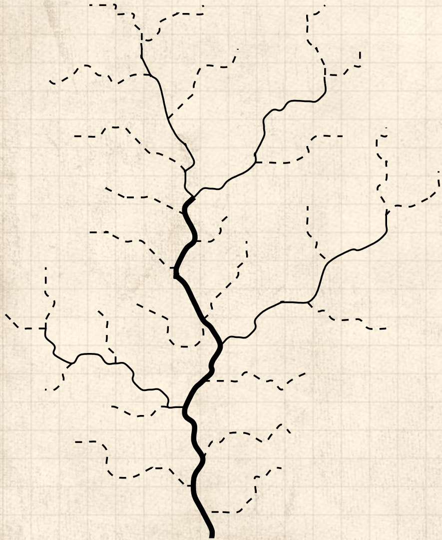
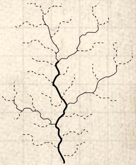


- Stream segments sum to give main stream lengths
- $$\ell_\omega = \sum_{\mu=1}^{\mu=\omega} s_\mu$$
- $P(\ell_\omega)$ is a convolution of distributions for the s_ω



Generalizing Horton's laws

- Sum of variables $\ell_\omega = \sum_{\mu=1}^{\mu=\omega} s_\mu$ leads to convolution of distributions:

$$N(\ell|\omega) = N(s|1) * N(s|2) * \cdots * N(s|\omega)$$

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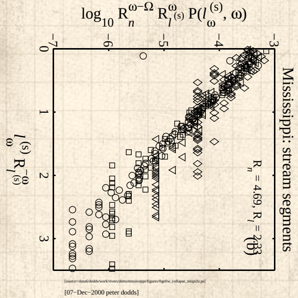
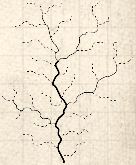


$$N(s|\omega) = \frac{1}{R_n^\omega R_\ell^\omega} F(s/R_\ell^\omega)$$

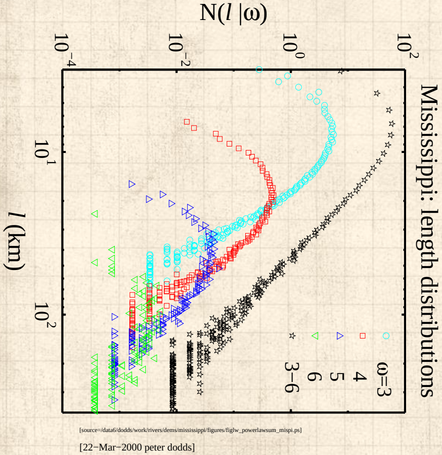
$$F(x) = e^{-x/\xi}$$

Mississippi: $\xi \simeq 900$ m.

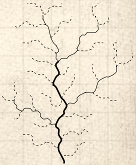


Generalizing Horton's laws

- Next level up: Main stream length distributions must combine to give overall distribution for stream length



- $P(\ell) \sim \ell^{-\gamma}$



Generalizing Horton's laws

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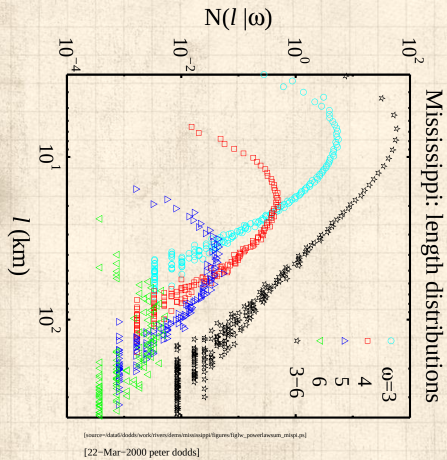
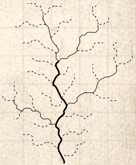
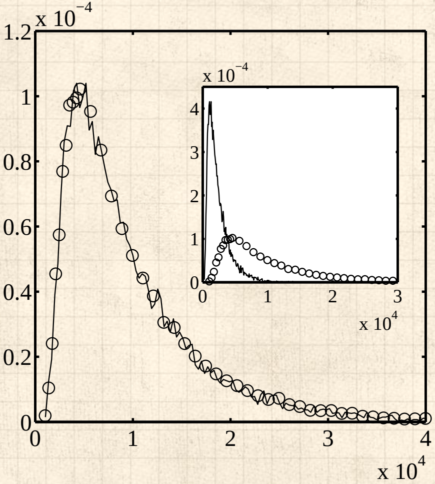


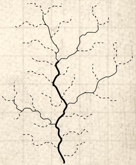
- $P(\ell) \sim \ell^{-\gamma}$
- Another round of convolutions [3]
- Interesting ...



Generalizing Horton's laws

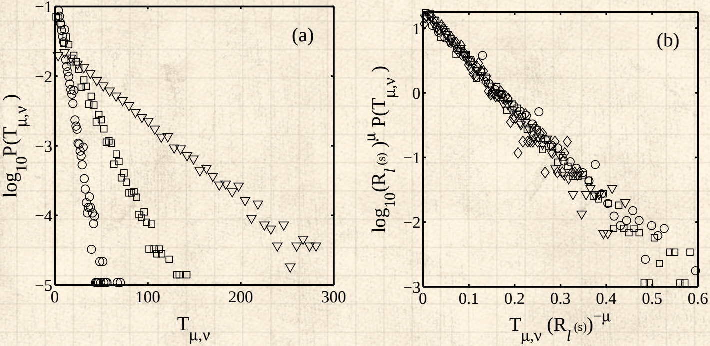
- Number and area distributions for the Scheidegger model [3]
- $P(n_{1,6})$ versus $P(a_6)$ for a randomly selected $\omega = 6$ basin.

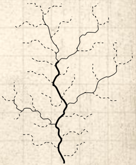




Generalizing Tokunaga's law

Scheidegger:

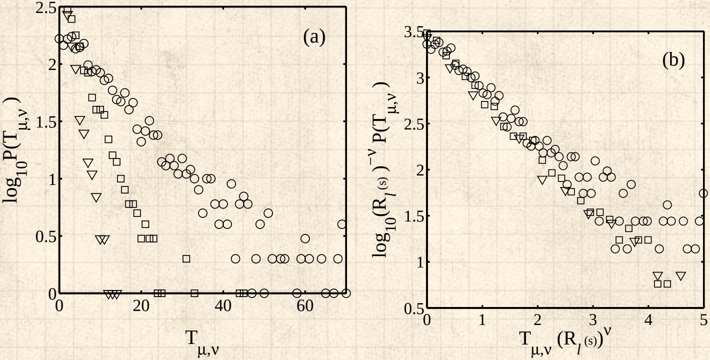




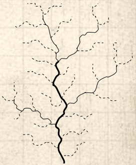
- Observe exponential distributions for $T_{\mu,\nu}$
- Scaling collapse works using R_s

Generalizing Tokunaga's law

Mississippi:



- Same data collapse for Mississippi ...



Generalizing Tokunaga's law

So

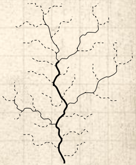
$$P(T_{\mu,\nu}) = (R_s)^{\mu-\nu-1} P_t \left[T_{\mu,\nu}/(R_s)^{\mu-\nu-1} \right]$$

where

$$P_t(z) = \frac{1}{\xi_t} e^{-z/\xi_t}.$$

$$\boxed{P(s_\mu) \Leftrightarrow P(T_{\mu,\nu})}$$

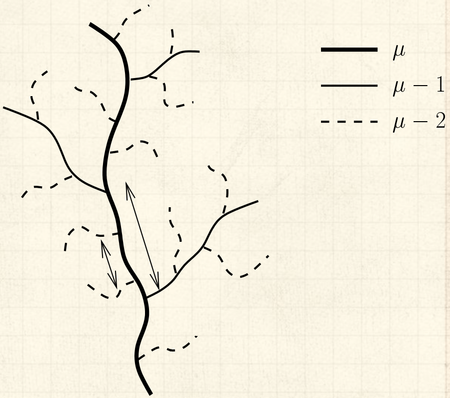
- Exponentials arise from randomness.
- Look at joint probability $P(s_\mu, T_{\mu,\nu})$.

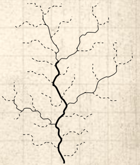


Generalizing Tokunaga's law

Network architecture:

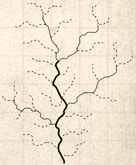
- Inter-tributary lengths exponentially distributed
- Leads to random spatial distribution of stream segments





Generalizing Tokunaga's law

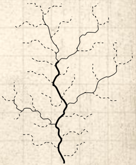
- Follow streams segments down stream from their beginning



Generalizing Tokunaga's law

- Follow streams segments down stream from their beginning
- Probability (or rate) of an order μ stream segment terminating is constant:

$$\tilde{p}_\mu \simeq 1/(R_s)^{\mu-1}\xi_s$$



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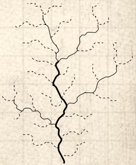

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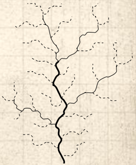

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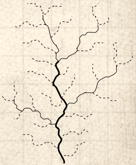
- $\Rightarrow$ random spatial distribution of stream segments



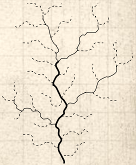
Generalizing Tokunaga's law

- Joint distribution for generalized version of Tokunaga's law:

$$P(s_\mu, T_{\mu,\nu}) = \tilde{p}_\mu \binom{s_\mu - 1}{T_{\mu,\nu}} p_\nu^{T_{\mu,\nu}} (1 - p_\nu - \tilde{p}_\mu)^{s_\mu - T_{\mu,\nu} - 1}$$

where

- p_ν = probability of absorbing an order ν side stream



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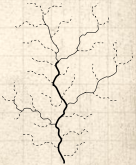

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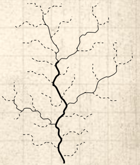
  where
  - p_ν = probability of absorbing an order ν side stream
  - $\tilde{p}_\mu$ = probability of an order μ stream terminating
- Approximation: depends on distance units of s_μ
- In each unit of distance along stream, there is one chance of a side stream entering or the stream terminating.



Generalizing Tokunaga's law

- Now deal with this thing:

$$P(s_\mu, T_{\mu,\nu}) = \tilde{p}_\mu \binom{s_\mu - 1}{T_{\mu,\nu}} p_\nu^{T_{\mu,\nu}} (1 - p_\nu - \tilde{p}_\mu)^{s_\mu - T_{\mu,\nu} - 1}$$

Generalizing Tokunaga's law

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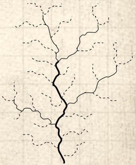
- Set $(x, y) = (s_\mu, T_{\mu,\nu})$ and $q = 1 - p_\nu - \tilde{p}_\mu$, approximate liberally.



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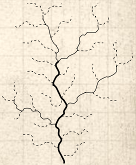
- Set $(x, y) = (s_\mu, T_{\mu,\nu})$ and $q = 1 - p_\nu - \tilde{p}_\mu$, approximate liberally.
- Obtain

$$P(x, y) = N x^{-1/2} \left[F(y/x)\right]^x$$

where

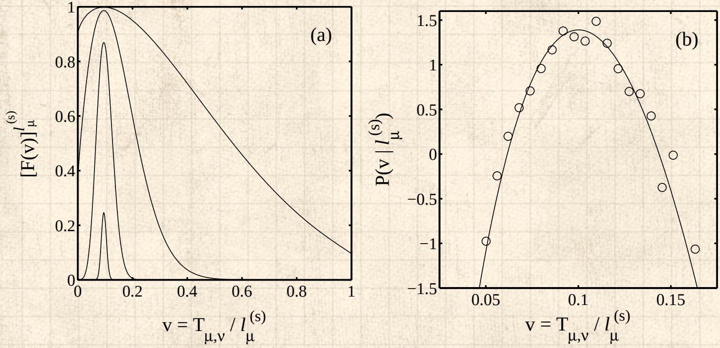
$$F(v) = \left(\frac{1-v}{q}\right)^{-(1-v)} \left(\frac{v}{p}\right)^{-v}.$$

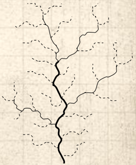


Generalizing Tokunaga's law

- Checking form of $P(s_\mu, T_{\mu,\nu})$ works:

Scheidegger:





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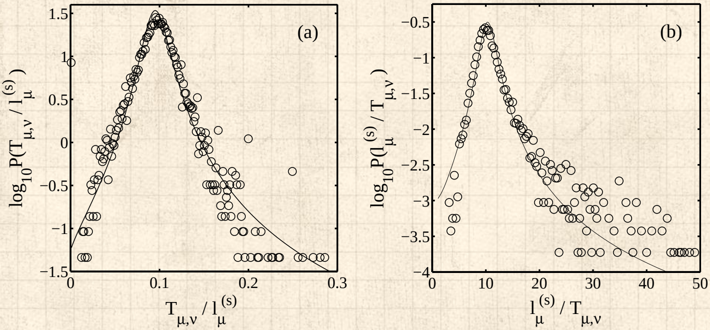

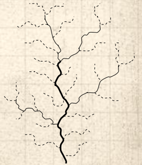

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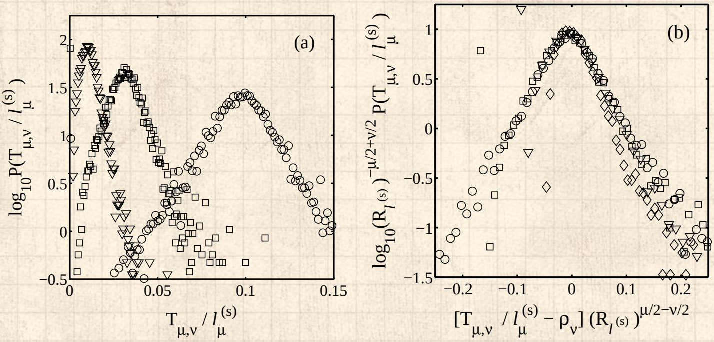
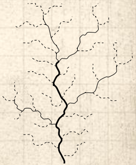
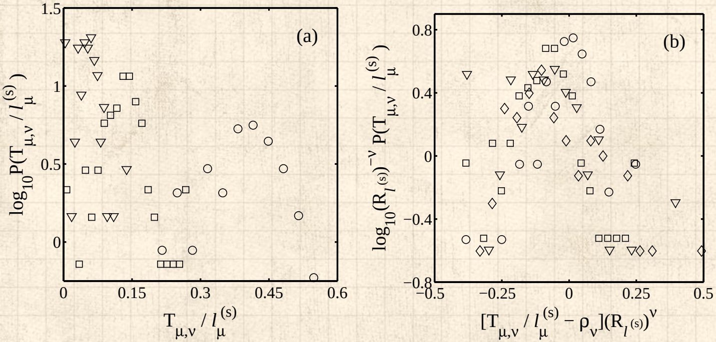


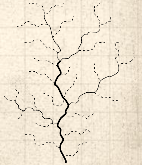


Generalizing Tokunaga's law

- Checking form of $P(s_\mu, T_{\mu,\nu})$ works:

Mississippi:






THE SUN
THE GOLDEN AGE OF REDUCTIONISM
THE MANIFESTO
WELL OF SCALES
THE LAWS OF DECAYING POWER
THE UNEXPECTED TRANSFIGURATION
MINISTRY OF RANDOM WALKS
THE RICH GET RICHER
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THE CHARMS OF THE MANY WRONG PATHS
THE BOOKS THAT SHOULD NOT BE OPENED
THE KNOWLEDGE OF DEAD MONKS
THE EMERGENCE OF STRUCTURE
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THE EMERGENCE OF THINKING
It was the best of times,
THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
THE NETWORKS COMPLEX
THE ELEMENTS OF WEBS
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THE ARK OF THE RANDOM NETWORK
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THE SMALLNESS OF WORLDS
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THE NETWORKS FREE OF SCALE
CLASSIFIED
PHOENIX
THE CONTAGION
THE CONFUSION OF CONTAGIONS
THE DISEASE OF RANDOM MIXING
THE UNENDING PANDEMICS
THE THRESHOLDS OF THE MIND
THE SOCIAL WILD
THE SOCIAL CONTAGION
THE RATIO OF GAIN
THE MECHANICS OF FAME
THE TALK OF FAME
THE STORIES CONTAGIOUS
THE JOHN DORY
THE ADJACENT NARRATIVES
THE STORYTELLERS
THE FATED ASTRAL PATH
THE PATHS OF UNIVERSALITY
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THE LAW OF OPTIMAL FORKS
THE CHURCH OF QUARTEROLOGY
THE TRUTHICIDE
THE FAMILY OF PANCAKE COWS
THE FAMILY OF SPHERICAL COWS
THE IMPROBABLE PACHYDERM
THE ILL-SCALING OF ALLOMETRIC BODIES
THE SUPPLY MOST FAIR
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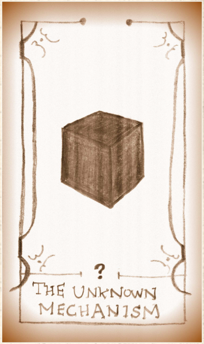
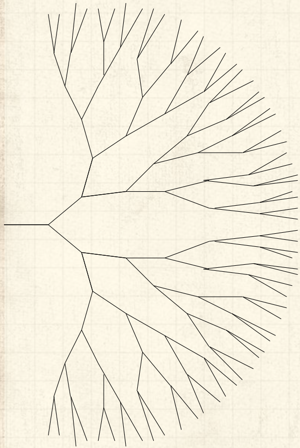

?
THE UNKNOWN MECHANISM

Models

Random subnetworks on a Bethe lattice [13]



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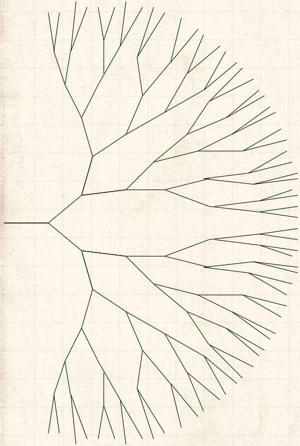

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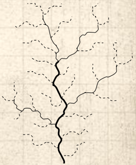

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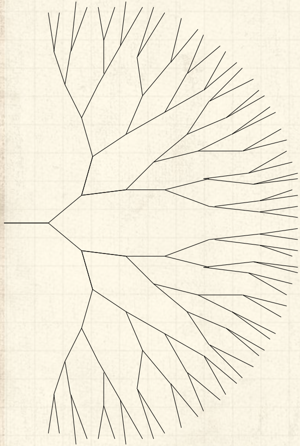

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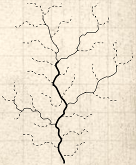

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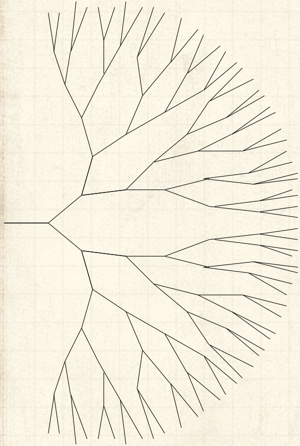

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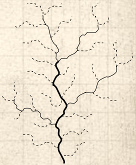

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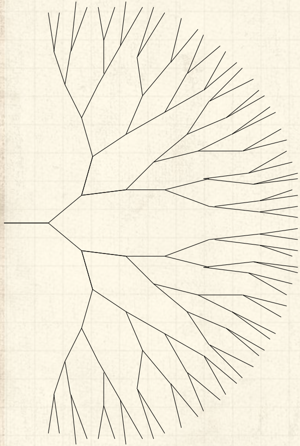

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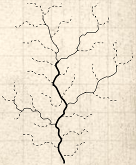

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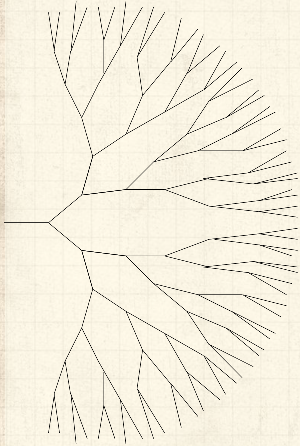

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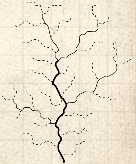

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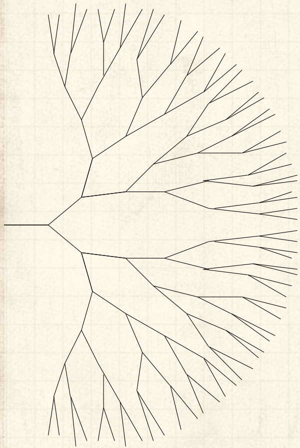

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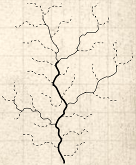
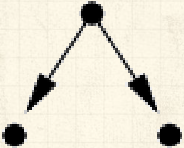
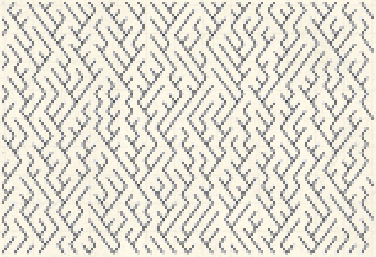


Scheidegger's model

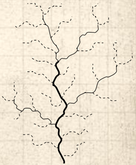
Directed random networks [11, 12]





$$P(\searrow) = P(\swarrow) = 1/2$$

- Functional form of all scaling laws exhibited but exponents differ from real world [15, 16, 14]



Optimal channel networks

Rodríguez-Iturbe, Rinaldo, et al. [10]

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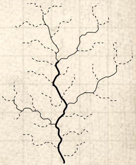

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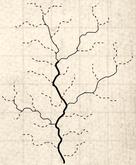

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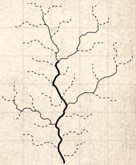

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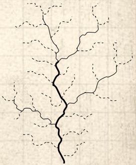

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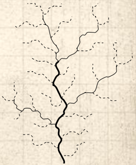
- And: Maritan et al. find basic universality classes are that of Scheidegger, self-similar, and a third kind of random network [8]



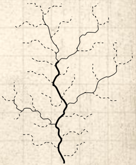
Theoretical networks

Summary of universality classes:

network	h	d
Non-convergent flow	1	1
Directed random	2/3	1
Undirected random	5/8	5/4
Self-similar	1/2	1
OCN's (I)	1/2	1
OCN's (II)	2/3	1
OCN's (III)	3/5	1
Real rivers	0.5–0.7	1.0–1.2

$h \Rightarrow \ell \propto a^h$ (Hack's law).

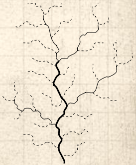
$d \Rightarrow \ell \propto L_{\parallel}^{d}$ (stream self-affinity).



Nutshell

Branching networks II Key Points:

- Horton's laws and Tokunaga's law all fit together.



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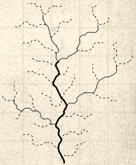

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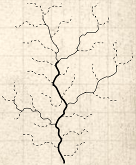

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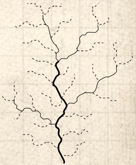
- For scaling laws, only $h = \ln R_\ell / \ln R_n$ and d are needed.
- Laws can be extended nicely to laws of distributions.



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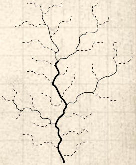
- For scaling laws, only $h = \ln R_\ell / \ln R_n$ and d are needed.
- Laws can be extended nicely to laws of distributions.
- Numerous models of branching network evolution exist: nothing rock solid yet ...?



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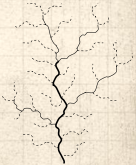

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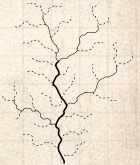

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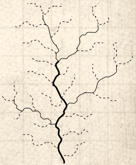

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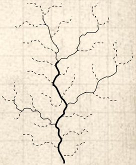

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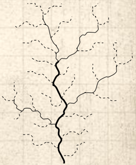

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